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Review

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MRI-derived radiomics models for diagnosis, aggressiveness, and prognosis evaluation in prostate cancer

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Abstract: Prostate cancer (PCa) is a pernicious tumor with high heterogeneity, which creates a conundrum for making a precise diagnosis and choosing an optimal treatment approach. Multiparametric magnetic resonance imaging (mp-MRI) with anatomical and functional sequences has evolved as a routine and significant paradigm for the detection and characterization of PCa. Moreover, using radiomics to extract quantitative data has emerged as a promising field due to the rapid growth of artificial intelligence (AI) and image data processing. Radiomics acquires novel imaging biomarkers by extracting imaging signatures and establishes models for precise evaluation. Radiomics models provide a reliable and noninvasive alternative to aid in precision medicine, demonstrating advantages over traditional models based on clinicopathological parameters. The purpose of this review is to provide an overview of related studies of radiomics in PCa, specifically around the development and validation of radiomics models using MRI-derived image features. The current landscape of the literature, focusing mainly on PCa detection, aggressiveness, and prognosis evaluation, is reviewed and summarized. Rather than studies that exclusively focus on image biomarker identification and method optimization, models with high potential for universal clinical implementation are identified. Furthermore, we delve deeper into the critical concerns that can be addressed by different models and the obstacles that may arise in a clinical scenario. This review will encourage researchers to design models based on actual clinical needs, as well as assist urologists in gaining a better understanding of the promising results yielded by radiomics.

Key words: Magnetic resonance imaging (MRI); Radiomics; Prostate cancer; Predictive model

1 Introduction

Prostate cancer (PCa) is the second most common malignancy in men, with an ever-increasing global incidence rate (Siegel et al., 2022). PCa remains clinically and biologically heterogeneous, making early detection, accurate risk stratification, and prognostic evaluation difficult. The current pattern for PCa assessment includes the prostate-specific antigen (PSA) test, digital rectal examination (DRE), transrectal ultrasound (TRUS)-guided biopsy, and magnetic resonance imaging (MRI) (Litwin and Tan, 2017). These approaches have certain limitations and fail to present an accurate and comprehensive judgment (French and Wallen, 2020). PSA suffers from relatively low specificity, which can be elevated in prostatitis and benign prostate hyperplasia (BPH) (Merriel et al., 2022). DRE is restricted by its high false positive rate. Biopsy, regarded as the gold standard for preoperative diagnosis of PCa, is typically performed through random sampling and is therefore incapable of reflecting the heterogeneity of all tumor foci. MRI is a standard technique for PCa detection and staging

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due to its superior soft tissue contrast and high resolution. However, the interpretation of the results relies heavily on the empirical and subjective judgment of radiologists.

Several traditional prediction models, such as the D'Amico tool, the University of California, San Francisco Cancer of the Prostate Risk Assessment (UCSF-CAPRA), and Kattan nomogram, have been proposed that integrate clinicopathological factors, including PSA, T stage, and biopsy results (D'Amico et al., 1998; Kattan et al., 1998; Cooperberg et al., 2005). In terms of precise risk evaluation and outcome prediction, a number of independent studies have reported validating these models, which can facilitate counseling of patients and clinical decision-making (Lughezzani et al., 2010; Ondracek et al., 2016; Brajtbord et al., 2017). However, few models have been endorsed and widely used in routine clinical practice except the D'Amico model. Although it is beyond the scope of this review to concentrate on radiomics models, we provide a brief overview and summary of those traditional predictive models applied to PCa because reviews regarding this topic are sparse (Campbell et al., 2017a). Furthermore, direct comparison with traditional models simplifies demonstration of the merits and disadvantages of radiomics models.

Multiparametric MRI (mp-MRI) provides both anatomical and functional sequences, which enhances the sensitivity and specificity of the localization and characterization of PCa lesions. mp-MRI plays an increasingly important role in PCa diagnosis, staging, and monitoring (Johnson et al., 2014). However, MRI does come with certain limitations because the image analysis relies mainly on anatomic changes, qualitative reporting paradigms, and subjective interpretations by radiologists, resulting in increased inter-reader variability and reduced reliability (Midiri et al., 2021).

Advance in artificial intelligence (AI) has made great strides in shifting the interpretation of medical image information from a qualitative assessment to one that is quantifiable and reproducible. AI constitutes the methodological basis of radiomics and plays a crucial role in every link of its workflow and in many aspects of clinical care (Bi et al., 2019). Radiomics is a powerful combination of medical images and AI technique, which is defined as the extraction and selection of huge quantitative features from medical images. The ultimate goal of this combination is to apply these features as robust and reliable imaging biomarkers so as to reflect the underlying intertumoral heterogeneity and biological phenotypes (Lambin et al., 2017; Acharya et al., 2018). Radiomics models based on salient biomarkers have the potential to assist PCa customized management in clinical procedures. Radiomics outperforms random sample biopsies and empirical image analysis by providing a quantitative, non-invasive, and cost-effective technique for characterizing the spatial and temporal information of tumor lesions (Spohn et al., 2021). However, there are a number of challenges to overcome in respect of its sophisticated workflow and overly professional methodology. Compared with traditional models based on clinicopathological factors, models using radiomic features compromise their role in actual clinical translation due to their decreased reproducibility and interpretability (Limkin et al., 2017). The aim of this review is to introduce and summarize studies of radiomics models based on MRI-derived features to aid the diagnosis, prognosis, and therapy response in PCa. We prefer models with sufficient potential for clinical utility and emphasize the role of radiomics in model establishment and clinical transformation.

2 Search strategy and article selection

The literature on radiomics and PCa published between 2012 and 2022 was searched using PubMed (https://pubmed.ncbi.nlm.nih.gov/?holding=icnpuhslib) and Web of Science (https://www.webofscience.com). The search strategy involved using a search line based on the following keywords: radiomics, radiogenomics, prostate cancer, predictive model, magnetic resonance imaging/MRI, artificial intelligence, deep learning, and machine learning. Papers related to radiomics in PCa diagnosis, aggressiveness, and prognosis evaluation were included in the review. In addition, literature related to conventional predictive models and published between 1995 and June 2022 was also searched through the same database based on keywords including prostate cancer, predictive model, outcome prediction, and biochemical recurrence (BCR). Further, a manual review of the reference list for the included literature was conducted to identify any more relevant works. Papers focused on other malignant tumors (such as bladder cancer

and breast cancer) and those without available full text were excluded.

3 Current role of MRI in the clinical PCa management

MRI has emerged as the most sensitive and specific imaging technique in clinical PCa management, expanding its role from tumor detection and staging to tumor monitoring, risk layering, and therapeutic planning (Costa, 2021). mp-MRI combines anatomical T1-weighted imaging (T1WI) and T2WI with functional diffusion-weighted imaging (DWI), dynamic contrast-enhanced MRI (DCE-MRI), and magnetic resonance spectroscopy imaging (MRSI), greatly improving the diagnostic ability of MRI. T1WI shows a uniform intermediate signal within the prostate without much differentiation of tumor and normal tissue. However, T1WI is useful for identifying the invasion of pelvic nodes, neurovascular bundles, and the prostatic capsule. T2WI provides high-resolution anatomical data appropriate for identifying tumor lesions and evaluating seminal vesicles, neurovascular bundles, and prostate margins. Tumors in T2WI typically manifest as a low-signal-intensity mass with fuzzy borders. DWI is a noninvasive technique based on the restriction of water molecule diffusion in the tumor region. Apparent diffusion coefficient (ADC) maps can be computed by an equation using different *b* values, where *b* value represents diffusion sensitivity factor, which refers to the degree of sensitivity to diffusion motion in MRI, and can determine image quality and lesion detection rate in ADC maps. Typically, a tumor displays a decreased value on the ADC map and a higher intensity on the DWI. The combination of ADC maps, DWI, and T2WI for PCa detection outperformed T2WI alone (Wu et al., 2012). DCE-MRI is an MRI technique that uses contrast agent injection to characterize the vascular characteristics of the prostate. A PCa lesion typically exhibits quicker uptake (enhancement) and washout than healthy tissue due to the angiogenesis associated with tumors, which stimulates and facilitates the growth of blood vessels. Despite the concern that the cost and inherent risks of DCE-MRI may increase because of the contrast agent, a previous study has demonstrated that it can be a useful addition to T2WI and DWI for aggressiveness assessment and local recurrence detection (Puech et al., 2013). MRSI uses two or three spatial dimensions to measure spectral profiles. These spectral patterns reveal the specific proton resonance frequencies of several metabolites. The diagnostic benefits of MRSI are outweighed by the fact that the scan time is too long, the spatial resolution is poor, and it is prone to artifacts (Sun et al., 2019). To standardize the image acquisition and interpretation procedure of prostate MRI, the Prostate Imaging Reporting and Data System (PI-RADS) was initially introduced in 2012 and updated in 2015 (v2) and 2019 (v2.1) (Turkbey et al., 2019). Despite some inconsistencies and limitations, PI-RADS has gained global acceptance in clinical and academic settings, with further application and validation ongoing. PI-RADS provides a detailed description of suspicious PCa in different MRI sequences, including T1WI, T2WI, DWI, and DCE-MRI using a Likert-like five-grade scoring system to evaluate the relative likelihood of the existence of a clinically significant PCa (csPCa).

In a clinical setting, MRI is used mainly to identify the location, regional invasion (capsule and seminal vesicle invasion), and distant metastasis (lymph node involvement and bone metastasis), all of which have a significant impact on decision-making. Early organ-localized PCa, for example, is the best indication for radical prostatectomy (RP), with a 5-year survival rate of 90% (Wallis et al., 2016). When capsule invasion and seminal vesicle invasion are present, neoadjuvant and adjuvant androgen deprivation therapies (ADTs) should be considered (Xylinas et al., 2010). Lymph node and bone metastasis impede RP, so systematic ADT and focal radiotherapy seem to be the rational choices. However, the 5-year survival rate drops dramatically below 50% for PCa with bone metastasis (Boevé et al., 2019). In addition, for patients with a Gleason score (GS) of 3+3 and PSA of <10 ng/mL, mp-MRI can be used for active surveillance (AS) eligibility evaluation and follow-up examination for patients (Lee et al., 2021). Moreover, MRI complements TRUS-guided biopsy by identifying a certain lesion that may be missed by ultrasound. A growing body of research has demonstrated that MRI-guided biopsy had higher detection rates of csPCa and a lower yield of insignificant PCa compared with TRUS-guided biopsy (Siddiqui et al., 2015).

4 Prostate radiomics: a brief overview

Although discussing radiomics workflow and methodology is out of the scope of this review, a brief retrospect is offered because of the basic assurance of the quality of radiomics studies they provide. The general radiomics procedure consists of four main steps (Fig. 1): (1) medical image acquisition, (2) region of interest (ROI) identification and segmentation, (3) feature extraction and selection, and (4) model establishment (Mayerhoefer et al., 2020). MRI image acquisition is the first step in radiomics. MRI is usually prescribed for almost every patient with suspected PCa in clinical practice, and provides a cost-effective way to acquire substantial imaging data without additional examination. ROI identification and segmentation in PCa is a crucial step because it defines the region for subsequent feature extraction. It is also a challenging step because of the variability and multifocality of PCa lesions. The question of how to select an ideal cancer focus for feature extraction is still under debate. The most commonly used method is to select the region with the largest volume and the highest PI-RADS score. However, the inconsistency between these two parameters makes rational decision-making difficult. Segmentation and delineation of PCa lesions based on digital pathological sections is an important direction, but there is a lack of relevant studies and encouraging data. ROI segmentation can be accomplished either manually, semi-automatically, or automatically. Despite the limitations of time-consumption and inter-reader variability, manual segmentation remains the most precise and standard approach for segmentation.

The huge number of quantitative imaging features leads to a long training time and reduced generalizability of the final model, thus necessitating subsequent dimensionality reduction using algorithms and feature elimination using data-driven thresholds. Data incapable of providing additional predictive information are discarded, while robust imaging biomarkers are retained based on three properties: repeatability, non-redundancy, and reproducibility. Following feature extraction and selection, model construction is the last step in the radiomics workflow. There are various statistical methods and deep learning algorithms

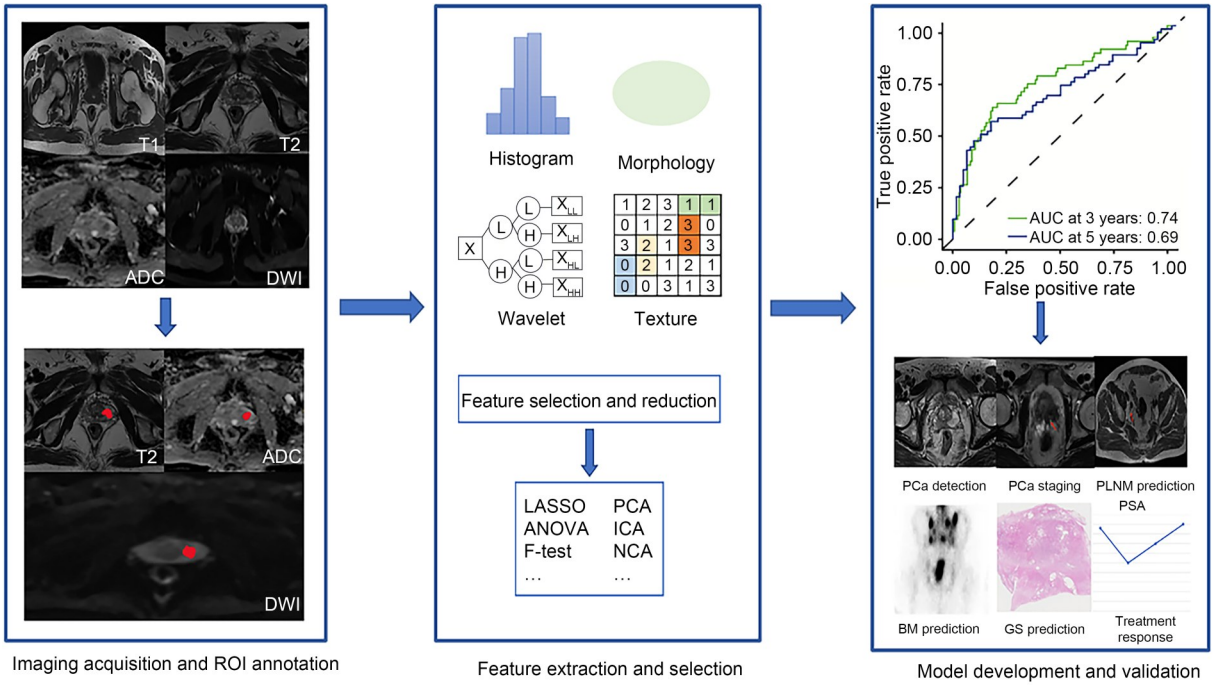

Fig. 1 Workflow of radiomics models used in PCa. The red zone shows the delineated tumor lesion. The two red arrows represent the seminal vesicle and lymph node invasion, respectively. ADC: apparent diffusion coefficient; AUC: area under the curve; ANOVA: analysis of variance; BM: bone metastasis; DWI: diffusion-weighted imaging; GS: Gleason score; ICA: independent component analysis; LASSO: least absolute shrinkage and selection operator; NCA: necessary condition analysis; PCa: prostate cancer; PCA: principle component analysis; PLNM: pelvic lymph node metastasis; ROI: region of interest.

for image data analysis and model building, such as logistic regression, support vector machine, decision tree, and conventional neural network. It is impossible to foresee which method will produce the best model, so it is strongly recommended to test several different models to select the best one. Internal and external validation should be performed as part of the model development scheme to ensure the robustness and generalizability of the model to targeted patients (Liu et al., 2020).

5 Conventional predictive models used in PCa

Numerous models have been proposed and evaluated for PCa patients in the last 20 years. The predictive accuracy, targeted people, and predictive outcomes vary for different tools. Several classic and extensively validated models which are considered generalizable and appropriate for clinical application are listed in Table 1. Our topic precludes further discussion of the detailed contents of the original and relevant derived models. For more information on those models, researchers can refer to the systematic reviews conducted by Campbell et al. (2017a, 2017b). Note that technological development, in-depth research, and updated guidelines have shifted the paradigm of PCa diagnosis and treatment to a more personalized and multimodal approach in the last 20 years. There is an urgent need to modify the traditional models and design new ones based on innovative molecular biomarkers to suit more complicated clinical scenarios. Several novel risk stratification and outcome prediction tools based on genetic biomarkers, such as the Decipher test, Oncotype Dx test, and Prolaris test, have been investigated (Ferro et al., 2021).

6 Novel MRI-radiomics models in the PCa management

Plenty of research has been conducted to identify and assess the radiomics features obtained from MRI for decision-making in PCa management. Some representative studies showing encouraging results and good potential for PCa diagnosis, risk stratification, staging, and treatment response prediction will be discussed here. In addition, we focus on the underlying clinical utility of the models, and discuss the possible roles they may play and the challenges they may present in actual clinical practice. The associated papers mentioned in the following sections are summarized in Table 2.

6.1 Radiomics models for assessing the diagnosis and aggressiveness of PCa

6.1.1 Radiomics models for csPCa detection (diagnosis)

PI-RADS and biopsy are two broadly used strategies for detecting and stratifying csPCa. However, the use of PI-RADS is restricted by unavoidable inter-reader variability, and biopsy, as an invasive approach, carries the risk of infection, hematuria, and urine retention (Berry et al., 2020). csPCa is defined as a tumor with a GS of ≥3+4, which requires active intervention instead of surveillance. Radiomics provides a non-invasive and quantitative method for distinguishing PCa and csPCa from benign prostate tissue. Wang et al. (2017) performed a study consisting of 54 PCa patients to determine whether an mp-MRI-based radiomics model could improve the diagnostic performance of PI-RADS v2 for csPCa recognition. They found that the radiomics model had a greater capability for distinguishing csPCa from normal peripheral zone (PZ) tissue than PI-RADS. The combination of radiomics features and PI-RADS significantly improved the predictive value for csPCa versus PZ tissue or transitional zone (TZ) tissue. Chen et al. (2022) compared a radiomics-based model with PI-RADS v2.1 in csPCa prediction. The results suggested that the radiomics model performed better than PI-RADS in csPCa identification regardless of the MRI modality. Perilesional radiomics features were investigated and compared with intralesional features by Zhang et al. (2021), with the aim of developing a nomogram to detect csPCa. Eight perilesional features were identified to improve the discrimination ability of the radiomics features, indicating that radiomics features extracted from the peritumoral region might also serve as meaningful imaging biomarkers (Zhang et al., 2021).

The presence of PI-RADS 3 prostate lesions is recognized as equivocal likelihood of csPCa occurrence, and most such lesions require active monitoring instead of immediate biopsy. Unfortunately, a certain percentage of PI-RADS 3 lesions will upgrade to PI-RADS 4 and PI-RADS 5, thus leading to a diagnosis and treatment delay (Brancato et al., 2021). Radiomics

Table 1 Conventional models for staging and outcome prediction used in PCa

Predictive model	Published year	Variables	Predicted outcome	Primary cohort	Accuracy	External validation (reference)
Kattan nomogram (Kattan et al., 1998)	1998	PSA, cT-stage, biopsy GS	5-year BCR-free probability	983 LPCa patients from single center treated with RP	AUC 0.79	Yes (Roupret et al., 2009) Yes (Isbarn et al., 2010) Yes (Ondracek et al., 2016) …
D'Amico risk groups (D'Amico et al., 1998)	1998	PSA, cT-stage, biopsy GS	PSA failure probability	1872 multi-center patients treated with RP, EBRT, or BT	NA	Yes (Lughezzani et al., 2010) Yes (Zelic et al., 2020) …
UCSF-CAPRA(s) score system (Cooperberg et al., 2005)	2005	PSA, cT-stage, GS, PPB, age	5-year BCR-free survival	1439 LPCa patients treated with RP from CaPSURE	C-index 0.66	Yes (Tamblyn et al., 2011) Yes (Punnen et al., 2014) Yes (Brajtbord et al., 2017) …
Stephenson nomogram (Stephenson et al., 2006)	2006	PSA, age, biopsy GS, cT-stage, numbers of positive and negative cores	1–10-year progression-free probability	1978 PCa patients from two medical centers treated with RP	C-index 0.79	Yes (Moreira et al., 2009) Yes (Isbarn et al., 2010) Yes (Boehm et al., 2016) …
J-CAPRA score system (Cooperberg et al., 2009)	2009	PSA, biopsy GS, TNM stage	PFS, CSS	19 265 PCa patients in J-CaP database and 13 740 PCa patients in CaPSURE database receiving PADT	PFS in J-CaP: C-index 0.71; CSS in CaPSURE: C-index 0.84	Yes (Shiota et al., 2015) Yes (Hu et al., 2018) …
MSKCC nomogram	2022 (dynamically updated)	PSA, age, biopsy GS, cT-stage, numbers of positive and negative cores	5-year BCR probability	11 552 PCa patients treated with RP in MSKCC	C-index 0.81	Yes (Yoneda et al., 2018) Yes (Zelic et al., 2020)
		PSA, biopsy GS, cT-stage	Lymph node involvement	11 552 PCa patients treated with RP in MSKCC	AUC 0.85	Yes (Hueting et al., 2018) Yes (Meijer et al., 2021) Yes (Soeterik et al., 2021)
		PSA, age, biopsy GS, cT-stage, numbers of positive and negative cores	Organ-confined cancer	6216 PCa patients treated with RP in MSKCC	AUC 0.70	Yes (Nesbitt et al., 2019)
		PSA, age, biopsy GS, cT-stage, numbers of positive and negative cores	Seminal vesicle invasion	6216 PCa patients treated with RP in MSKCC	AUC 0.85	Yes (Hinev et al., 2011) Yes (Nesbitt et al., 2019)
		PSA, biopsy GS, cT-stage	Extracapsular extension	11 552 PCa patients treated with RP in MSKCC	AUC 0.66	Yes (Hinev et al., 2011) Yes (Nesbitt et al., 2019)

AUC: area under the curve; BCR: biochemical recurrence; BT: brachytherapy; CaPSURE: Cancer of the Prostate Strategic Urologic Research Endeavor; C-index: concordance index; CSS: cancer-specific survival; cT-stage: clinical T stage; EBRT: external beam radiotherapy; GS: Gleason score; J-CaP: Japan Study Group of Prostate Cancer; J-CAPRA: Japan Cancer of the Prostate Risk Assessment; MSKCC: Memorial Sloan Kettering Cancer Center; NA: not available; PADT: primary androgen deprivation therapy; PCa: prostate cancer; LPCa: localized PCa; PFS: progression-free survival; PPB: percentage of positive biopsy; PSA: prostate-specific antigen; RP: radical prostatectomy; TNM: tumor node metastasis; UCSF-CAPRA: the University of California, San Francisco Cancer of the Prostate Risk Assessment.

Table 2 Radiomics models used for the diagnosis, risk stratification, and staging of PCa

Reference	Model type	Objective	MRI modality	Results	External validation
Radiomics models for PCa diagnosis					
Wang et al., 2017	SVM model	PCa detection	T2WI, DCE, RESOLVE-DWI	Models established on radiomics features and PI-RADS score provided higher predictive accuracy than model based on either radiomics features or PI-RADS for the differentiation of PCa from normal PZ and TZ tissues.	No
Bagher-Ebadian et al., 2019	ANN model	PCa detection	T2WI, DWI	The radiomics model differentiated tumor lesions from normal tissues with AUC, PPV, and NPV of 0.94, 0.95, and 0.92, respectively.	No
Qi et al., 2020	LR model	PCa detection	T2WI, DWI, DCE	The combined model incorporating radiomics features, clinical parameters, and PI-RADS v2 exhibited a good predictive value to identify PCa in patients with PSA in 4–10 ng/mL, with AUC values of 0.96 and 0.93 in the primary and validation cohorts, respectively.	Yes
Woźnicki et al., 2020	RML model	PCa detection	T2WI, DWI	The model combining radiomics features and clinical parameters achieved high predictive AUC for the differentiation of malignant from benign prostatic lesions (AUC=0.89) and of csPCa from ciPCa (AUC=0.84).	Yes
Hu et al., 2021	LR model	PCa detection	T2WI, ADC, DWI	The mixed model combining clinical parameter PSA and radiomics features yielded best predictive performance for PCa detection compared with radiomics model and clinical model (AUC values at mixed:radiomics:clinical= 0.94:0.93:0.81 in the training set and 0.93:0.92: 0.74 in the validation set).	No
Radiomics models for the GS prediction (aggressiveness assessment) of PCa					
Fehr et al., 2015	RML model	csPCa identification and GS classification	T2WI, ADC	The radiomics model distinguishes GS 6 (3+3) from GS≥7 cancers with 0.93 accuracy and distinguishes GS 7 (3+4) from GS 7 (4+3) with 0.92 accuracy for cancers occurring in both the PZ and TZ.	No
Chaddad et al., 2018	RF model	GS prediction	T2WI, DWI	The radiomics model combining JIM and GLCM analyses provided the best performing AUC with values of 0.78 for GS≤6, 0.82 for GS=3+4, and 0.65 for GS≥4+3.	No
Hectors et al., 2021	RF model	csPCa prediction in PI-RADS 3 lesions	T2WI	The RF model constructed from the T2WI radiomics features demonstrated good and statistically significant AUC of 0.76 (P=0.022) for prediction of csPCa in the test set.	No
Min et al., 2019	LASSO-LR model	csPCa identification	T2WI, ADC, DWI	The radiomics model discriminated csPCa and ciPCa with an AUC of 0.87, sensitivity of 0.88, and specificity of 0.75 in the training cohort, and 0.82, 0.84, and 0.73 in the test cohort.	No
Parra et al., 2019	LR model	csPCa identification	DCE, ADC	Radiomics model based on features derived from DCE and ADC differentiated csPCa vs. ciPCa with AUC values of 0.88 vs. 0.82 in intra and inter-institution analysis, respectively.	No
Li et al., 2022	LR model	csPCa identification	T2WI, DWI	The radiomics model (AUC=0.98) and combined clinical-radiomics model (AUC=0.98) achieved greater predictive efficacy than the clinical model (AUC=0.79) to predict csPCa.	No
Chen et al., 2019	LR model	PCa detection and high-grade PCa identification	T2WI, ADC	Radiomics models based on T2WI and ADC features achieved AUC values of 1.00 for PCa detection and 0.93 for high-grade PCa identification, outperforming PI-RADS.	No

To be continued

Table 2 (continued)

Reference	Model type	Objective	MRI modality	Results	External validation
Zhang YS et al., 2020	MLR nomogram	csPCa identification	T2WI, ADC, DWI	Radiomics nomogram incorporating radiomics features and ADC value demonstrated favorable classification capability with an AUC of 0.95 (training set), 0.93 (internal validation set), and 0.84 (external validation group) for discriminating csPCa from ciPCa.	Yes
Bleker et al., 2020	LR model, RML model	csPCa identification	T2WI, ADC, DCE	The radiomics model with features from T2WI+DWI+DCE had an AUC of 0.87 to identify csPCa in PZ.	No
Gong et al., 2020	LR model	csPCa identification	T2WI, DWI, ADC	The radiomics model based on features from DWI achieved the best predictive ability for distinguishing high-grade PCa from low-grade PCa with AUC values of 0.80 in the training cohort and 0.79 in the test cohort.	No
Hou et al., 2020	RML model	csPCa identification in PI-RADS 3 lesions	T2WI, ADC, DWI	The RML-i model integrating radiomics features of T2WI, ADC, and DWI all together outperformed the RML-ii model integrating independent radiomics feature from above-mentioned sequences in identification of csPCa in PI-RADS 3 lesions.	No
Shao et al., 2020	DRL model	GS prediction	T2WI-FS	The radiomics model outperformed biopsy results to acquire the final GS of RP pathology, which reduced the upgrading rate by 27.9% and downgrading rate by 6.4% from biopsy GS to RP pathology.	Yes
Brancato et al., 2021	LR model	csPCa detection	T2WI, ADC	The radiomics model classified PCa lesions (GS> (3+3)) in PI-RADS 3 lesions with an AUC of 0.80, sensitivity of 0.51, and accuracy of 0.71.	No
Han et al., 2021	SVM and LR model	csPCa prediction	ADC	Radiomics models based on automatic segmentation on ADC maps exhibited the same diagnostic efficacy as manual segmentation, biopsy, and PI-RADS.	No
Castillo et al., 2021	RML model	High-grade PCa detection	T2WI, DWI, ADC	The radiomics model obtained a mean AUC of 0.75 in the multi-center setting to identify high-grade PCa, outperforming the radiologists' performance using PI-RADS with a mean AUC of 0.47 on the same subset.	Yes
Brunese et al., 2020	CNN model	PCa detection and GS prediction		The radiomics model was generated for GS prediction equal to 0.98, 0.97, 0.99, and 0.98 with regard to GS 3+3, GS 3+4, GS 4+3, and GS 4+4 prediction, respectively. Moreover, the proposed model was also able to discriminate between prostate cancerous and healthy areas with an accuracy of 0.96.	No
Gong et al., 2022	MLR model	GS prediction	T2WI, ADC, DCE	The model based on whole prostate gland radiomics features reached a C-index of 0.73 and an average AUC of 0.79 in the validation cohort, with a toleration of a segmentation boundary deviation of 2 mm without significant performance degradation.	No
Li et al., 2022	MVLR nomogram	csPCa identification	T2WI, ADC, DCE	Radiomics nomogram using radiomics features and PSAD showed an excellent predictive value with AUC values of 0.94, 0.88, and 0.91 in the training group, test group, and validation group respectively to differentiate csPCa from ciPCa in PI-RADS 3 lesions.	Yes
Chen et al., 2022	SVM model	csPCa identification	DCE	The radiomics model outperformed the PI-RADS v2.1 in the diagnosis of csPCa regardless of whether bpMRI or mp-MRI was used.	No

To be continued

Table 2 (continued)

Reference	Model type	Objective	MRI modality	Results	External validation
Radiomics models for the staging of PCa					
Stanzione et al., 2019	RML model	EPE prediction	T2WI, ADC	The radiomics model showed a percentage of correctly classified instances of 82%, an AUC of 0.88, a sensitivity of 0.82, and specificity of 0.80 to predict the presence of EPE.	No
Ma et al., 2019	LASSO model	EPE prediction	T2WI	Radiomics models yielded AUC values of 0.90 and 0.88 in the training and validation cohorts for the perdition of EPE, respectively, and outperformed the radiologists' assessment (AUC: 0.60–0.70) in the validation cohort.	No
Losnegård et al., 2020	RF model	EPE prediction	T2WI, ADC, DCE	The radiomics model predicted EPE with an AUC of 0.74, which was comparable to radiology interpretation with an AUC of 0.75 and better than the clinical nomogram (MSKCC) with an AUC of 0.67.	No
Cuocolo et al., 2021	SVM model	EPE prediction	T2WI, ADC	The radiomics model reached an overall accuracy of 0.83 in the training set and accuracy of 0.79 and 0.74 in two external test sets, respectively, which was comparable to the radiologists' performance.	Yes
Bai et al., 2021	LR model	EPE prediction	T2WI, ADC	The integrated models combining radiomics signature from PTR with clinical characteristics performed better in EPE detection than corresponding radiomics signatures in the internal validation set (AUC: 0.72 vs. 0.67), but performed similarly in the external validation set.	Yes
Hou et al., 2021	RF model	PLNM prediction	T2WI, DWI, ADC	The PLNM-Risk model integrating clinicopathologic, radiological parameters, and radiomics features accomplished good diagnostic values with AUC of 0.93, 0.92, and 0.76 in the training/validation, internal test, and external test cohorts, respectively.	Yes
Bourbonne et al., 2021	CNN model	PLNM prediction	T2WI, ADC	The model combining radiomics features and clinical variables reached a C-index of 0.89 for lymph node involvement, providing added predictive performance compared to present conventional predicting model.	No
Wang YR et al., 2019	LR model	BM identification	T2WI, DCE-T1WI	Radiomics model combined with clinical risk factors yielded the highest AUC of 0.92 for BM identification.	No
Zhang WJ et al., 2020	MVLR nomogram	BM prediction	DCE-T1WI T2WI, DWI	Radiomics nomogram established on radiomics features and clinical parameters had good discrimination and calibration in the training cohort with an AUC of 0.93, and an AUC of 0.92 in the validation cohort.	No

ADC: apparent diffusion coefficient; ANN: artificial neural network; AUC: area under the curve; BM: bone metastasis; CAPRA: Cancer of the Prostate Risk Assessment; C-index: concordance index; CNN: convolutional neural network; DCE: dynamic contrast enhancement; DRL: deep reinforcement learning; DWI: diffusion-weighted imaging; EPE: extra-prostatic extension; FS: fat suppression; GLCM: grey level co-occurrence matrix; GS: Gleason score; JIM: joint intensity matrix; LASSO: least absolute shrinkage selector operator; LR: logistic regression; MLR: multi-class linear regression; MRI: magnetic resonance imaging; bpMRI: biparametric MRI; mp-MRI: multiparametric MRI; MSKCC: Memorial Sloan Kettering Cancer Center; MVLR: multiple variable logistic regression; NPV: negative predictive value; PCa: prostate cancer; ciPCa: clinically insignificant PCa; csPCa: clinically significant PCa; LPCa: localized PCa; PI-RADS: Prostate Imaging Reporting and Data System; PLNM: pelvic lymph node metastasis; PPV: positive predictive value; PSA: prostate-specific antigen; PSAD: prostate-specific antigen density; PTR: peritumoral region; PZ: peripheral zone; RI-PADS: Prostate Imaging Reporting and Data System; RESOLVE: Readout segmentation of long variable echo-trains; RF: random forest; RML: radiomics machine learning; RP: radical prostatectomy; SVM: support vector machine; T1WI: T1-weighted imaging; T2WI: T2-weigthed imaging; TZ: transition zone.

has the capability to detect csPCa in PI-RADS 3 lesions. A study conducted by Hectors et al. (2021) included 240 patients with PI-RADS 3 lesions. A random forest (RF) model based on radiomics features derived from T2WI outperformed models based on clinical parameters. To differentiate csPCa from clinical insignificant PCa (ciPCa) in PI-RADS 3 lesions, Li et al. (2020) recently proposed and externally validated a radiomics nomogram combining radiomics features and PSA density (PSAD). The nomogram achieved encouraging predictive values with areas under the curves (AUCs) of 0.94 in the training group, 0.88 in the test group, and 0.91 in the validation group. The clinical usefulness of the nomogram was further confirmed by decision curve analysis (DCA) (Li et al., 2020). Biopsy decision is still clinically challenging for patients with PSA levels in the grey zone (4–10 ng/mL). A model was constructed and externally validated by Qi et al. (2020) to identify PCa patients in the grey zone for the purpose of reducing unnecessary biopsies. The combined model incorporating a multi-imaging fusion model, age, PSAD, DRE, and PI-RADS v2 score performed best in both the primary and validation cohorts. The calibration curve showed good agreement between the predicted and expected probabilities of PCa (Qi et al., 2020).

6.1.2 Radiomics models for GS prediction (aggressiveness assessment)

The GS is one of the most important pathological biomarkers for PCa prognosis that allows for stratification of patients into different risk groups. Biopsy is used to determine the preoperative GS in current clinical practice. Several studies have attempted to predict GS using radiomics features. A study of GS prediction by Chaddad et al. (2018) showed that the radiomics model was predictive of the biopsy GS in a cohort of 99 patients. Five imaging signatures were confirmed to be independent factors of GS. The best AUC was achieved based on the joint intensity matrix (JIM) and grey level co-occurrence matrix (GLCM) analysis using an RF algorithm (Chaddad et al., 2018). Shao et al. (2020) developed and externally validated a radiomics model to reduce the inconsistency between biopsy and postoperative GS based on a multicenter dataset. The T2WI sequence was used, and the radiomics model achieved a better predictive accuracy than biopsy results for final pathological GS, which significantly reduced the upgrading and downgrading risks from biopsy.

6.1.3 Radiomics models for extra-prostatic extension prediction (aggressiveness assessment)

The identification of extra-prostatic extension (EPE) is critical for treatment option and preoperative planning. Despite the widespread use of PI-RADS, MRI-based assessment of extracapsular extension (ECE) remains limited due to variable accuracy (Krishna et al., 2018). Radiomics exploits a new approach to EPE prediction through quantitative feature analysis and deep learning algorithms. Stanzione et al. (2019) first took advantage of radiomics features using texture analysis and machine learning for EPE detection in a cohort of 39 PCa patients. The classifier model achieved a promising result with an AUC of 0.88. Ma et al. (2019) compared the predictive performance of radiomics features with that of the radiologist in ECE detection based on 210 patients with pathology-confirmed ECE status. Seventeen stable features selected from 1619 extracted features were used for model building, yielding a higher AUC than the judgment by the radiologists in the validation cohort.

6.1.4 Radiomics models for pelvic lymph node metastasis prediction (aggressiveness assessment)

Pelvic lymph node metastasis (PLNM) is a critical prognostic factor affecting therapeutic options and prognosis evaluation. Several models, such as the Memorial Sloan Kettering Cancer Center (MSKCC) nomogram, Briganti score, and Partin score, have been proposed and are recommended by the European Association of Urology (EAU) guidelines for PLNM risk stratification and extended pelvic lymph node dissection (ePLND) candidate identification (Meijer et al., 2021). Hou et al. (2021) established a novel PLNM-Risk model to predict the lymph node status and compared its performance with the Briganti score and MSKCC. The PLNM-Risk model, which combines radiomics features with clinicopathologic and radiological interpretation, achieved satisfying diagnostic performance with AUC values of 0.93 in the training/validation cohort and 0.76 in the external test cohort. When the PLNM-missing rate was controlled at less than 2% according to the EAU guidelines, the PLNM-Risk model offered a higher number of ePLND spared at a lower cost of the number of PLNM missed than the MSKCC and Briganti nomograms. Bourbonne

et al. (2021) revealed that a model combined with radiomics and clinical features through a neural network provided added predictive performance compared to existing models such as the Partin, Roach, and MSKCC models regarding PLNM prediction. Furthermore, the net benefit associated with the use of this innovative radiomics-based model compared to currently available tools for PLNM recognition was demonstrated by DCA.

6.1.5 Radiomics models for bone metastasis prediction (aggressiveness assessment)

Bone metastasis is a fatal event for PCa patients, indicating a loss of curative opportunity and rising mortality. The current bone metastasis diagnostic system relies mainly on emission computed tomography (ECT) and positron emission tomography-computed tomography (PET-CT), which are limited respectively by low specificity and high expense. Zhang WJ et al. (2020) identified 12 selected radiomics features that were significantly related to bone status among 160 newly diagnosed PCa patients. A nomogram integrated with radiomics biomarkers and clinical factors demonstrated good discrimination and calibration in both training and validation sets for bone metastasis status. Wang YR et al. (2019) also proposed that radiomics features could be used as biomarkers to predict pretreatment bone metastasis in a "watchful waiting" PCa cohort. This study found 15 radiomics signatures significantly correlated with bone metastasis. The signatures were used to generate a model for bone metastasis prediction with an AUC of 0.92.

6.2 Radiomics models for prediction of prognosis and therapeutic responses

The natural history of PCa biochemical and clinical relapse after definitive therapy is very heterogeneous. Accurate outcome prediction and precise treatment options for PCa remain challenging, even in the genetics era. Radiomics exploits a novel approach to reveal the underlying tumor biological characteristics and further facilitate prognosis assessment and individualized management.

Several studies have been conducted to investigate the role of radiomics features on the prognosis and evaluation of treatment responses after RP and radiotherapy (RT) for PCa. Gnep et al. (2017) identified Haralick features to predict BCR based on a cohort of 74 PCa patients treated by external beam RT (EBRT). The radiomics model achieved a promising result for BCR prediction by combining the most significant features, reaching a concordance index (C-index) of 0.90. Small Zone Emphasis-Grey Level Small Zone Matrix (SZE_{GLSZM}), a feature derived from ADC, was devised by Bourbonne et al. (2019, 2020) for BCR prediction among 107 high-risk PCa patients following RP. SZE_{GLSZM} was predictive of BCR and BCR-free survival (AUC of 0.76 and an accuracy of 0.78 in the primary cohort and an accuracy of 0.76 in external validation). Yan et al. (2021) trained and externally validated a radiomics model in a multi-center cohort of 485 PCa patients receiving RP. The radiomics model developed on 702 features extracted from T2WI achieved a C-index of 0.802 in both training and validation groups, which outperformed conventional predicting models such as the CAPRA post-Surgical (CAPRA-S) score, the National Comprehensive Cancer Network (NCCN) model, and Gleason grade group systems. The relevant papers on this topic are summarized in Table 3.

7 Current dilemma and future prospective for clinical translation of radiomics models

Despite the rapid development of deep learning and MRI-based radiomics, there are still some obstacles to overcome before radiomics can be integrated into clinical routines in both methodology and application. Radiomics entails a series of essential but complex steps to extract imaging features from MRI from different vendors and with different sequence parameters. It is difficult to standardize the radiomics pipeline due to the variability of MRI modality and radiomics methodology, which impedes the consistency of results and external validation from multicenter studies. Radiomics methodology is based on deep learning algorithms, whose focus is on performance improvement rather than interpretability. The image features selected by deep learning may be significantly related to a certain outcome. However, due to the black-box nature of deep learning, it appears challenging for clinicians to explain the non-intuitive features to patients in clinical settings. In addition, the reproducibility and stability of image features are other issues that need to be further investigated. Changes in each link of the radiomics workflow, such as ROI delineation, feature extraction, and algorithm selection, will result in

Table 3 Radiomics models for prediction of prognosis and therapeutic responses in PCa

Reference	Model type	Objective	MRI modality	Results	External validation
Gnep et al., 2017	RF model	BCR prediction after EBRT	T2WI, ADC	Twenty-eight T2WI Haralick features and four geometrical features were significantly associated with BCR. The radiomics model combining these most powerful features using RF obtained a C-index of 0.90 for BCR prediction for LPCa in PZ.	No
Shiradkar et al., 2018	ML model	BCR prediction after RP/RT	T2WI, ADC	The radiomics model obtained an AUC of 0.84 in training cohort and 0.73 in validation cohort for BCR prediction after RP/RT.	Yes
Bourbonne et al., 2019	ML model	BCR prediction after RP	T2WI, ADC	The radiomics feature was identified to predict the BCR for high-risk PCa patients after RP.	Yes
Wu et al., 2019	SVM model	Therapeutic response prediction after CIRT	T2WI, ADC	The radiomics model achieved an AUC of 0.88 for therapeutic response prediction after CIRT.	No
Zhong et al., 2020	Adaboost model	BCR prediction after RP	T1WI, T2WI, DWI	The radiomics model predicted the BCR of LPCa patients after RT with an AUC of 0.99 in training set and 0.73 in the test set.	No
Li et al., 2021	CPH nomogram	BCR prediction after RP	T2WI, ADC	The radiomics model combining imaging features and clinicopathologic variables yielded a higher C-index of 0.77 for BCR prediction after RP than CAPRA or Decipher.	No
Yan et al., 2021	DL model	BCR prediction after RP	T2WI	The radiomics model achieved C-index of 0.802 for BCR prediction in both primary and validation cohorts, outperforming traditional models like CAPRA-S and NCCN.	Yes

ADC: apparent diffusion coefficient; AUC: area under the curve; BCR: biochemical recurrence; CAPRA: Cancer of the Prostate Risk Assessment; CAPRA-S: CAPRA Post-Surgical; C-index: concordance index; CIRT: carbon iron radiotherapy; CPH: Cox Proportional-Hazards; DL: deep learning; DWI: diffusion-weighted imaging; RT: radiotherapy; EBRT: external beam RT; PCa: prostate cancer; LPCa: localized PCa; ML: machine learning; NCCN: National Comprehensive Cancer Network; PZ: peripheral zone; RF: random forest; RP: radical prostatectomy; SVM: supporting vector machine; T2WI: T2-weighted imaging.

substantial variation in the acquired features. The standardization of image acquisition and processing, feature extraction, and selection will facilitate the stable presentation and external verification of image biomarkers. Moreover, key information should be sufficiently described to allow comparisons among models and validation. The Imaging Biomarker Standardization Initiative (IBSI) standard was proposed in 2020 to establish a robust methodological radiomics framework (Zwanenburg et al., 2020). Stanzione et al. (2020) proposed the Radiomics Quality Score (RQS) as a point-based system for identifying the critical aspects of the radiomics workflow. RQS consists of 16 items and generates a score out of 36 to reflect the scientific rigor and weaknesses of radiomics research, and to a certain extent, the translational capacity of the models. RQS and IBSI were both recommended to enhance the reproducibility and quality control of radiomics research to encourage cross-center collaboration and extensive clinical implementation.

The issues impeding the clinical adoption of radiomics can be divided into two categories. First, the insufficiency of the radiomics pipeline and AI methodology is one aspect limiting clinical applicability. The time-consuming process of image acquisition and ROI delineation, as well as opaque feature selection, are frequently denounced by researchers. Second, a big data set is a prerequisite for AI algorithm selection and model development. However, the management and quality control of big data sets are tough tasks, and variation in data quality will have a significant impact on algorithm optimization and model efficacy. Researchers have investigated solutions to overcome these obstacles. For instance, automatic segmentation aided by AI may help boost the effectiveness of identifying a specific ROI. Unsupervised and self-supervised methods show promise in reducing the time investment problem since definite labeling is not required. It has become mainstream for radiomics-related studies to provide more detailed information

about the model construction in an effort to improve interpretability and transparency (Bi et al., 2019). Data must be quality assured by qualified personnel prior to storage. Standardization of the data formats is necessary for effective data sharing. Another aspect restricting the potential clinical utility of radiomics is that it must be tailored to a specific clinical situation. There are, however, several common issues that should be further discussed. For instance, how should we proceed when the outcomes of radiomics-based assessment diverge from those based on expert experience? Considering the propensity of AI for learning and evolution, human expertise will continue to play a pivotal role in the initial decision-making phase until the model stabilizes. Improvements made to the model during the application process will gradually reveal its true worth and eventually improve and perfect the traditional diagnostic mode.

Although there is a long way to go before radiomics can challenge the dominance of troika (PSA, MRI, and biopsy) for PCa evaluation in clinical PCa management, radiomics provides a solid foundation and a substantial addition to existing diagnostic modalities. Firstly, radiomics aids PI-RADS in distinguishing (cs)PCa from benign tissue and contributes to PCa staging by determining the status of the capsule, lymph node, and bone. In addition, radiomics may complement the PSA test and assist in providing a rational biopsy inclusion standard for suspected PCa patients with slightly elevated PSA levels (Qi et al., 2020). Radiomics models have demonstrated their enormous potential to discern GS and may therefore clinically benefit those low-risk patients by avoiding definitive therapy.

In terms of csPCa and GS prediction, more studies with postoperative pathology as a reference are still needed. The ultimate goal is to explore the possibility of non-invasive radiomics overcoming the biopsy bias and eventually replacing it to guide clinical decision-making. The radiomics modality reduces puncture-related complications and shortens the waiting time before surgery. However, radiomics-based decisions regarding curative therapy must be made with extreme caution, as urinary incontinence and erectile dysfunction may complicate such interventions. This requires radiomics to offer comparable accuracy to the biopsy results. Adequate and efficient communication is required to ensure that the patients accept the commensurable treatment strategies without pathology.

For the application of radiomics to EPE and bone metastasis prediction, the clinical diagnosis stage at which radiomics intervention should be used needs to be determined. The diagnosis made by the radiologist may still be the initial step. A reasonable strategy is to apply radiomics to hard-to-diagnose patients to generate additional imaging labels. Radiomics can benefit junior radiologists and urologists in the diagnosis of complex cases and relieve senior experts from heavy review work. This protocol provides a viable method for junior physicians to gain experience and enhance their work efficiency.

As for prognosis and treatment response prediction, the key lies in the comparison with the traditional model based on clinicopathological indicators. Conventional models are widely validated and used by researchers and urologists. To be widely accepted, radiomics models, which are relatively difficult to develop and validate, must have significantly higher predictive accuracy than conventional models. Radiomics is committed to more precise evaluation rather than empirical and rough evaluation, despite the fact that it requires specific technology and time-effort. The role of radiomics in treatment response should be equivalent to that of target genetic analysis. The role of radiomics in this context is to reliably anticipate the patient's reaction to some treatment approaches, such as ADT, chemotherapy, and radiotherapy, so as to provide tailored treatment strategies. There are two components to treatment response prediction: prognosis prediction and treatment toxicity prediction. Treatment toxicity prediction has received less attention from researchers than prognosis prediction, with studies focusing mainly on the prediction of harm to neighboring organs induced by PCa radiotherapy. For example, Abdollahi et al. (2018) investigated the potential role of radiomics features from rectal MRI to predict the rectal toxicity induced by intensity-modulated radiation therapy (IMRT) for PCa patients. The radiomics model based on pre-IMRT T2 features showed the best AUC of 0.68. Although current research data on predicting therapeutic toxicity reactions are limited, it is believed to be a promising area for future study.

Multiple aspects of radiomics rely heavily on AI, including automatic segmentation, feature selection, and model construction. Previous research has investigated the use of deep learning algorithms for the automatic segmentation of prostate glands or cancer lesions

to increase work efficiency (Kalantar et al., 2021). Convolutional neural networks (CNNs), fully convolutional networks (FCNs), and U-net make up the deep learning architecture for automatic segmentation. Wang B et al. (2019) proposed a novel FCN with a group dilated convolution to automatically segment the MRI prostate. The method achieved a Dice similarity coefficient (DSC) of 0.86±0.04 in the internal dataset and 0.88±0.05 in the public dataset. To et al. (2018) introduced a deep dense multi-path CNN that follows the framework of the encoder-decoder design to segment the prostate on MRI images. The proposed network achieved DSCs of 95.11 and 89.01 in two independent datasets, respectively, and the segmentation results closely matched those provided by human experts. In addition, the application of AI algorithms involves feature selection and model construction. Classification tasks can be accomplished using methods like logistic regression, RF, and support vector machine, while prognostic subjects can be handled with Cox regression. Each algorithm has unique advantages and limitations, so the selection should be based on the specific research issue. For example, the results generated by logistic regression have probabilistic interpretations, and the weights are related to feature importance. The interpretability of the logistic model is good, but it is insufficient to deal with complex patterns. Support vector machine can be used for complicated tasks with kernel methods, but the data may be overfitted by complex kernels, and the model's interpretability is compromised (Sun et al., 2019). Notably, algorithm selection based on experience is unreliable, and there is no solid method to predict the predictive efficacy of a particular algorithm for real application in advance. Therefore, it is advisable to use various algorithms simultaneously in a study and to choose the one with the best performance. Finally, AI-assisted evaluation systems are critical elements for clinical translation. An intelligent platform based on AI and radiomics can be envisioned. It would work in conjunction with a hospital's imaging system to automatically capture patient-specific images and then execute image processing, data extraction, and analysis to produce a persuasive report. This is a complex process that may require human assistance. The support of AI, on the other hand, will significantly reduce the human effort.

To explore the feasibility of radiomics models, studies with a prospective design urgently need to be conducted. Prospective studies can provide high-level evidence to support the broad acceptance and use of radiomics, which is an important direction in the future. The ultimate goal of radiomics is to be applied to the clinical diagnosis and treatment process. Therefore, using radiomics in a real-world clinical setting is the best option for model validation. However, prospectively designed clinical trials are still scarce. NCT05024162 is an ongoing prospective clinical trial using radiomics features to predict pathological grade groups (based on the GS). The researchers will develop a radiomics predictive model for grade group prediction and compare it to the biopsy results evaluated by pathologists. It is estimated that sixty patients with a recent diagnosis of PCa will enroll in this study. The outcomes of this prospective research are eagerly anticipated (Kucharczyk, 2021).

8 Conclusions

We have reviewed MRI-derived radiomics models with a focus on PCa diagnosis, aggressiveness, and prognosis evaluation. In summary, radiomics has a bright future in the precise care of PCa patients, but equally faces a series of problems that need to be solved. The primary ways to overcome such obstacles are the ongoing advancement of AI technology and the standardization of the radiomics process. The focus should be not only on how to improve model performance by refining AI methodology, but also on how to provide a user-friendly platform to help radiomics transfer into routine clinical practice.

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Author contributions

Xuehua ZHU, Lizhi SHAO, Zenan LIU, and Jide HE searched the literature; Xuehua ZHU and Lizhi SHAO drafted the manuscript; Zhenyu LIU, Jiangang LIU, Hao PING, and Jian LU contributed to the design and revision of this manuscript. All authors have read and approved the final manuscript.

Compliance with ethics guidelines

Xuehua ZHU, Lizhi SHAO, Zhenyu LIU, Zenan LIU, Jide HE, Jiangang LIU, Hao PING, and Jian LU declare that they have no conflict of interest.

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